This **BEAM Architecture** expands upon the original BEAM formulation in the following respects: (1) incorporation of physical models, (2) integration of symbolic reasoning components, (3) statistical and stochastic modeling of individual signals (augmenting or supplanting prior wavelet-based modeling), (4) trending to failure for individual signals and cross-signal features, and (5) enumeration of results using an expert system.

feature-extraction components. This split allows BEAM to consider very complex faults in the system, including interference faults or miscommunication that escape univariate detection methods, while retaining robustness in poorly redundant systems or in the face of gross nonlinerity.

The components of BEAM described in the figure are summarized as follows:

- The model filter combines sensor data with predictions from a real-time physical model. The inclusion of physical models, where available, is the most efficient way to incorporate domain knowledge into signal-based data analysis.
- The symbolic data model interprets status variables and commands to provide an accurate, evolving picture of the system mode and requested actions.
- The coherence-based fault detector tracks the cobehavior of temporally varying quantities to expose changes in internal operating physics.

- The dynamical invariant anomaly detector tracks parameters of individual signals to sense subtle deviations and predict near-term behavior.
- The Informed Maintenance Grid (IMG) studies evolution of cross-channel behavior over the medium- and long-term operation of the system. It tracks consistent subthreshold deviations and exposes deterioration and loss of performance.
- The prognostic assessment yields a forward projection of individual signals, based upon their extracted parameters. It also provides a useful short-term assessment of impending faults and loss of functionality.
- The causal system model is a rule-based connectivity model designed to improve isolation of fault sources and identification of actor signals.
- The interpretation layer collates observations from all separate components and submits a single fault report in a

format useable by recovery software, planners or other AI software, and/or human operators.

This work was done by Ryan Mackey, Mark James, Han Park, and Michail Zak of Caltech for **NASA's Jet Propulsion Laboratory**. *Further information is contained in a TSP [see page 1].*

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Determining Direction of Arrival at a Y-Shaped Antenna Array

The direction is computed from differences among times of arrival of signals.

John F. Kennedy Space Center, Florida

An algorithm computes the direction of arrival (both azimuth and elevation angles) of a lightning-induced electromagnetic signal from differences among the times of arrival of the signal at four antennas in a Y-shaped array on the ground. In the original intended application of the algorithm, the baselines of the array are about 90 m long

and the array is part of a lightning-detection-and-ranging (LDAR) system. The algorithm and its underlying equations can also be used to compute directions of arrival of impulsive phenomena other than lightning on arrays of sensors other than radio antennas: for example, of an acoustic pulse arriving at an array of microphones.

The underlying equations express the differences among the times of arrival as functions of the inner products of (1) the unit vector of the direction of arrival and (2) the unit vectors along the baselines of the array. To obtain a solution for the unit vector (and thus, equivalently, the azimuth and elevation angles) of the direction of arrival,

the underlying equations are combined and modified into a matrix formulation that is amenable to a least-squares solution.

The value of the inner product calculated from the measured difference between the times of arrival of the signal at the two antennas on each baseline specifies a circle in the sky upon which nominally lies the apparent point in the sky from which the signal came. Thus, from the time-of-arrival measurements on all three baselines of the Y-shaped array, it is possible to specify three circles in the sky, all of which nominally contain the apparent point in the sky from which the signal came. Nominally, all three circles would intersect at a single point in the sky corresponding to the direction of arrival. In practice, random measurement errors prevent the three circles from intersecting at a single

point; instead, they intersect to define a small trianglelike patch of sky. The least-squares-error solution corresponds to a point near the triangle, such that sum of squares of distances between the solution point and each circle in the sky is the least possible value.

This algorithm has been verified on both synthetic data and measurement data recorded by a prototype short-baseline LDAR system. An analysis of errors revealed that the azimuth error depends only on elevation and that the elevation error is small except near the horizon. Further analysis showed that the addition of a vertical baseline (two additional antennas mounted on the top and bottom of a tower) would add little of value to the measurements and calculations since the LDAR source points are typically above 20° elevation.

The primary source of error in the algorithm is the simplifying assumption that the signal originates at an infinite distance. While this assumption is never strictly true, it provides an acceptable approximation as long as the distance of the signal source is much greater than the length of the baselines. The least-squares approach also reduces this error.

An additional equation that takes account of the curvature of a wavefront arriving from a source at a finite distance has been derived and found to be accurate at close range. An algorithm that would solve iteratively for azimuth, elevation, and range of the source has been proposed but not tested.

This work was done by Stan Starr of **Kennedy Space Center**. *Further information is contained in a TSP [see page 1].* KSC-12059

Self-Supervised Dynamical Systems

Mathematical models describe coupled motor and mental dynamics.

NASA's Jet Propulsion Laboratory, Pasadena, California

Some progress has been made in a continuing effort to develop mathematical models of the behaviors of multi-agent systems known in biology, economics, and sociology (e.g., systems ranging from single or a few biomolecules to many interacting higher organisms). This effort at an earlier stage was reported in "Characteristics of Dynamics of Intelligent Systems" (NPO-21037), *NASA Tech Briefs*, Vol. 26, No. 12 (December 2002), page 48.

To recapitulate from the cited prior article: Living systems can be characterized by nonlinear evolution of probability distributions over different possible choices of the next steps in their motions. One of the main challenges in mathematical modeling of living systems is to distinguish between random walks of purely physical origin (for instance, Brownian motions) and those of biological origin. Following a line of reasoning from prior research, it has been assumed, in the present development, that a biological random walk can be represented by a nonlinear mathematical model that represents coupled mental and motor dynamics incorporating the psychological

concept of reflection or self-image. The nonlinear dynamics impart the lifelike ability to behave in ways and to exhibit patterns that depart from thermodynamic equilibrium. Reflection or self-image has traditionally been recognized as a basic element of intelligence.

The nonlinear mathematical models of the present development are denoted self-supervised dynamical systems. They include (1) equations of classical dynamics, including random components caused by uncertainties in initial conditions and by Langevin forces, coupled with (2) the corresponding Liouville or Fokker-Planck equations that describe the evolutions of probability densities that represent the uncertainties. The coupling is effected by fictitious information-based forces, denoted supervising forces, composed of probability densities and functionals thereof.

The equations of classical mechanics represent motor dynamics — that is, dynamics in the traditional sense, signifying Newton's equations of motion. The evolution of the probability densities represents mental dynamics or self-image. Then the interaction between the physi-

cal and metal aspects of a monad is implemented by feedback from mental to motor dynamics, as represented by the aforementioned fictitious forces. This feedback is what makes the evolution of probability densities nonlinear. The deviation from linear evolution can be characterized, in a sense, as an expression of free will.

It has been demonstrated that probability densities can approach prescribed attractors while exhibiting such patterns as shock waves, solitons, and chaos in probability space. The concept of self-supervised dynamical systems has been considered for application to diverse phenomena, including information-based neural networks, cooperation, competition, deception, games, and control of chaos. In addition, a formal similarity between the mathematical structures of self-supervised dynamical systems and of quantum-mechanical systems has been investigated.

This work was done by Michail Zak of Caltech for **NASA's Jet Propulsion Laboratory**. *Further information is contained in a TSP [see page 1].* NPO-30634